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ORIGINAL ARTICLE

Re-approaching fuzzy cognitive maps to increase the knowledge of a system

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Abstract
Fuzzy cognitive maps is a system modeling methodology which applies mostly in complex dynamic systems by describing causal relationships that exist between its parameters called concepts. Fuzzy cognitive map theories have been used in many applications but they present several drawbacks and deficiencies. These limitations are addressed and analyzed fuzzy cognitive map theories are readdressed. A new novel approach in modelling fuzzy cognitive maps is proposed to increase the knowledge of the system and overcome some of its limitations. The state space approach is used for the new model to disaggregate the concepts into different categories. The disaggregation of the concepts into state concepts, input concepts and output concepts is mathematically formulated. The proposed method and the new model is used for the calculation of a building's energy consumption and the management of its load. Simulations are performed as a case study testing the new proposed method. The problem of the high energy consumption of the building sector is studied using the new fuzzy cognitive map model. Discussions of the obtained results along with future research directions are provided.

Keywords Energy efficiency · Building energy management · Knowledge · Fuzzy cognitive maps · State equations

1 Introduction

Climate change and growing shortages of resources, not only of energy, are the big challenges of our time. In the energy sector, many countries around the world are dependent on imported energy. In the European Union (EU), for example, 50% of energy consumed today is imported, a figure expected to reach 70% by 2030. Considering the previous percentages the need for efficient and sustainable energy usage becomes evident; this need has been underlined in the EU energy policy 2020. Buildings have the biggest share of the world wide primary energy consumption; 36% in the USA, 42% in Europe and more than 50% in Singapore. Worldwide up to 50% of the distributed electricity is used in buildings. Electricity production today represents 31% of total global fossil fuel use and around 40% of all energy related CO_2 emissions. For these reasons, energy crisis is commonly accepted to be among the most severe problems the world is facing nowadays. As such, measures to increase the energy efficiency of buildings can have a positive impact to energy saving and consequently to global climate protection. The need for increased energy savings raises some difficult questions: do we have the necessary and useful models, methods, proper equipment, techniques, software tools and governmental policies to address these challenging and difficult tasks. In addition, do we use the proper mix of renewable energy sources in an intelligent and efficient way to meet the total energy demand of a region? And how all these are effectively connected to the energy savings of buildings? Groumpos and Mpelogianni (2016) have analyzed the issues and variables that affect the overall energy performance of a building, the various methods and techniques which have been used to meet certain energy efficient and savings of a building as well as the lack of a unified mathematical model that can consider all variables and other related concepts regarding the energy efficiency of the building.

To answer the above-mentioned questions and concerns this paper proposes the use of the modeling methodology of fuzzy cognitive maps (FCMs) to address and investigate the energy efficiency of buildings. Fuzzy cognitive maps are a soft computing methodology for modeling complex

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systems which exploits the knowledge and experience of experts, providing its users with the ability to encounter problems in the same way human mind does; using a conceptual procedure which can include ambiguous or fuzzy descriptions (Bourgani et al. 2014). They were introduced by Kosko in 1986 as an extension of Axelrode's Cognitive maps (Axelrode 1976), (Kosko 1986). FCMs originated as a combination of Fuzzy Logic and Neural Networks and can be illustrated as a causal graphical representation consisting of interrelated concepts. Fuzzy cognitive maps combine the graphical representation and calculation method of Neural Networks and the linguistic variables approach of fuzzy logic (Papageorgiou and Stylios 2008). Using the causal relationship between concepts-nodes FCMs succeed in representing knowledge in a symbolic way and modeling the behavior of systems containing elements with complex relationships, which sometimes can be hidden or illegible; a great advantage of FCMs is the use of experts who due to their knowledge and experience of the system can help identify relations between the various concepts that are not always obvious by simply studying the mathematical model of the system. They, therefore, offer an economical, flexible, fast and versatile approach to a variety of problems (social, political, economic, environmental and mechanical) which are extremely complex and a purely mathematical approach, could be time consuming, laborious and wasting of many resources. Fuzzy cognitive maps even though they have a history of only 30 years, are one of the most promising methodologies in modeling complex dynamic systems (CDSs) which are characterized with (a) non-linearities (b) high degree of complexity and (c) a large number of uncertainties. As it is shown in Mpelogianni and Groumpos (2015), Ntarlas and Groumpos (2015), Groumpos and Anninou (2012), Vergini et al. (2015), they have been used in a large variety of systems (energy systems, medicine, economy, sociology, etc) with very good results. However, as the use of FCMs increases, a number of limitations of their classic approach arose. Some of these limitations are: (a) lack of knowledge of the system; the nature of the concepts (inputs, states, outputs) is not taken into consideration (Groumpos and Gkountroumani 2014) (b) dependence on experts; the FCMs method is highly dependent on the experts' intervention for the Fuzzy Cognitive Maps design (Papageorgiou et al. 2004; Schneider et al. 1995), (c) disability of self-learning; the design of adaptation approaches is much more difficult because of their complex structure and variability (Vaščák and Madarász 2010), (d) definition of the causality; how can the causality be defined with a high degree of credibility (Koulouriotis et al. 2001), (e) calculation equation; how can a unified value, to describe the total change caused to one concepts by all the others, can be calculated (Mpelogianni and Groumpos 2016a, b), (f) ignorance of time factor; how can a different time delay for each causal relation be implemented (Schneider et al. 1995), (g) use of the sigmoid function and interpretation of the results; the use of the curve to fit the results to the desired interval can distort the final interpretation of the results (Karagiannis and Groumpos 2013; Bueno and Salmeron 2009; Mpelogianni and Groumpos 2016a, b). Due to the aforementioned limitations, the need for a new approach of fuzzy cognitive maps emerges.

Until today many successful efforts have been made to overcome these well-known drawbacks of fuzzy cognitive maps, especially those related with the knowledge of the system and the dependence of the experts. Song et al. (2010b), have proposed the implementation of FCMs using fuzzy neural networks to construct them directly from data, thus making them independent of expert knowledge. Fuzzy neural networks are very powerful tool regarding the modeling and control of complex dynamic systems both on their own as well as in cooperation with fuzzy cognitive maps (Chen and Teng 1995; Song et al. 2010a). In this paper, we are proposing a different approach to overcome the drawbacks of FCMs. One that utilizes the structure of state space approach. Our goal is to propose a new approach which is going to overcome some of these limitations and offer more accurate results and a better view and knowledge of the system by combining the knowledge of the experts along with the data available for the system.

The outline of the article goes as follows. Section 2 analyses the energy problem; focusing on the building sector, worldwide. Section 3 makes a brief introduction of the existing Fuzzy Cognitive Maps method. In Sect. 4 the problems we are going to address are presented and a new approach of Fuzzy Cognitive Maps is being proposed. In Sect. 5 the energy model used in the simulation study of this paper is being presented. In Sect. 6 simulation results of the classic as well as the new approach are presented. Finally, in Sect. 7 these results are discussed, conclusions are presented and future research topics are proposed.

2 World energy outlook

The precipitous fall in oil prices, continuous geopolitical instability and the ongoing climate changes are witness to the dynamic nature of today's energy situation. In a time of so much uncertainty and confusion, understanding the implications of the shifting energy landscape for economic and environmental goals and for energy security is vital to future stability and sustainable economic growth for all nations. As stressed in the introduction the world undergoes a severe energy crisis. As shown in Fig. 1, while the conventional energy resources march towards their end the renewable energy sources have not yet been able to replace them; a fact that has severe consequences not only to the future of

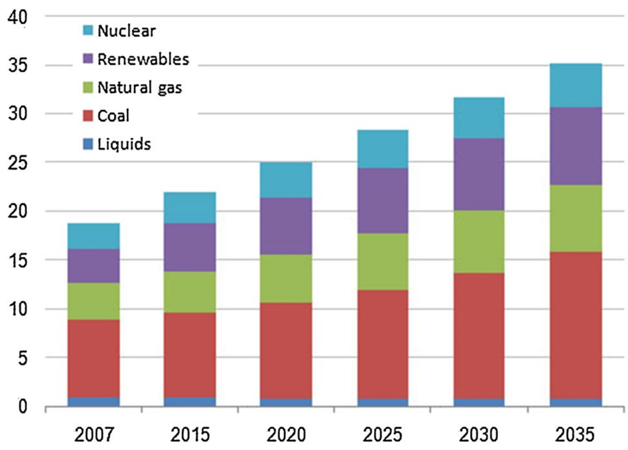


Fig. 1 Energy Use by sector until 2035 Source: OECD

the energy production but to the environment as well, as the gas emissions still increase rapidly. So now more than ever it is very important to concentrate our efforts to develop solutions that will lead to an environment friendly and energy independent future.

The world data are not encouraging. From 2001 to 2004 there was a large increase to primary energy consumption; 1.3% for Europe, 1.1% for USA, 2.2% for South and Central America, 5.3% for the Middle East, 3.7% for Africa and 8.6% for Asia Pacific, which implies an overall increase of the world's energy consumption by 3.7%. Even with the lowest possible estimations a 2% average annual growth in energy demand, is going to double by 2037 and triple by 2050 (Filippín and Larsen 2007). Furthermore, the International Energy Agency (IEA) (Aitken 2003) warns against the risk that current events of world politics distract those who are taking decision for energy policies from recognizing and tackling the longer-term signs of stress that are emerging in the world energy system.

More information and data regarding this report can be found in the ISES report (Aitken 2003). There is though, one remark worth mentioning, the anticipation of an increase of the use of renewable energy sources (RES); they are expected to account for nearly half of the global increase in power generation by 2040 and overtake coal as the leading source of electricity.

Wind power accounts for the largest share of growth in RES-based generation, followed by hydropower and solar technologies. Nevertheless, as the share of wind and solar PV in the worlds power mix quadruples, their integration becomes more challenging both from a scientific-technical and market perspective. It is also worth mentioning the historic Paris agreement, of the 2015 United Nations Climate Change Conference, COP 21 or CMP 11, held in Paris, France, from 30th November to 12th December 2015. This conference resulted to a global agreement on the reduction of climate change, the text of which represented a consensus of the representatives of the 196 parties attending it. According to the organizing committee at the outset of the talks, the expected key result was an agreement to set a goal of limiting global warming to less than 2 degrees Celsius (°C) compared to pre-industrial levels. The agreement calls for zero net anthropogenic greenhouse gas emissions to be reached during the second half of the twenty-first century. In the adopted version of the Paris Agreement, the parties will also "pursue efforts to" limit the temperature increase to 1.5 °C. The 1.5 °C goal will require zero emissions sometime between 2030 and 2050, according to some scientists. The achievement of the aforementioned goals depends highly on the political actions which will be taken from all the participants of the agreement, but also to the scientific community to provide the necessary tools to make energy reduction a reality.

2.1 Buildings' energy aspects

As mentioned in the introduction a great amount of the total energy consumed nowadays is used by the building sector. Thus, to achieve the highest percentage of energy reduction, the building performance should be taken into consideration in the early design stages. For this reason, access to all information defining a building such as its form, materialization and technical systems is necessary. Common, document-based CAD planning environments do not support this integrated view of a building. In machine engineering, the concept of semantic data models was established in the 1970s, connecting logical and physical information (Schlueter and Thesseling 2009). This concept was adopted by the building industry and used to develop generic building description systems, later called "building product models" (Eastman 1976, 1999). Since 2002, the term of building information models has been widespread. Building information models enable storing multidisciplinary information within one virtual building representation. A building's information model is a richer repository than a set of drawings, since it has the ability to store different types of information. These types of information include geometric, semantic and topological information. Geometric information directly relates to the building form in three dimensions. Semantic information describes the properties of components such as u-values of walls. Topological information captures the dependencies of components. Apart from the building information model, the performance analysis is also important to investigate the energy consumed by a building and take actions for its reduction. Schlueter and Thesseling (2009), have conducted an extensive description on the software tools developed both for a building information modelling and its performance analysis. Even though, all the models, approaches and software tools which have been developed are very good for studying, analyzing and designing parts and/or the performance of a building, they are not capable to address the generic concept of energy efficiency from a broader mathematical approach, specifically that of intelligence. Thus, the need to explain the term of intelligence and especially that of Intelligent Buildings emerges.

3 Intelligent buildings

3.1 Intelligent buildings' definition

As the scientific interest turned towards the building sector, the need to define what is an intelligent building (IB) became evident. However, due to the rapid evolvement of the building industry and information technology, the formulation of a single and widely accepted definition of Intelligent Buildings proved to be a rather difficult task. For this reason, the various definitions of IBs were divided into three categories according to the approach used to study them.

These categories are listed below:

1. Services based definitions.
2. System based definitions.
3. Performance based definitions.

In the effort of helping the reader understand the concept of the Intelligent Building, the various definition categories with emphasis to the one used in this paper will be explained below.

3.1.1 Services based definitions

In this category, IBs are studied from the point of view of the services offered and their quality. According to the Japanese Intelligent Building Institute (JIBI), "An IB is a building with the service functions of communication, office automation and building automation, and is convenient for intelligent activities. Services to users are emphasized." For the Japanese, there are four key aspects regarding an IB:

1. Acting as a core for receiving and transmitting information and supporting efficient management.
2. Providing a satisfactory and convenient working environment.
3. Optimization of building management to offer low cost but attractive administrative services.
4. Adaptability to the quick changing sociological environment, working demands and various business strategies (Wang 2010).

3.1.2 System based definitions

This category includes the definitions concerning the technology (software and equipment) of IBs. A typical definition which best describes this category is the one proposed by the Chinese IB Design Standard (GB/T50314–2000): "IBs provide building automation, office automation and communication network systems, and an optimal composition integrates the structure, system, service and management, providing the building with high efficiency, comfort, convenience and safety to users."

Another system based IB definition used by some developers and professionals is the one that characterizes the IBs as the "3A"; building automation (BA), communication automation (CA) and office automation (OA) (Wang 2010).

3.1.3 Performance based definitions

The final category studies the expected performance of the building. The two definitions that best describe this category will be presented. The first is given by the European Intelligent Building Group (EIGB) and the second by the Intelligent Building Institute (IBI) based in the United States. The first one describes an Intelligent Building as one that offers its users the most effective environment and on the same time uses and manages its resources in a manner that ensures the reduction of the cost due to the use of equipment and facilities. While the second defines an IB as a building which provides a productive and cost-effective environment through the optimization of its four basic elements including structures, systems, services and management and the interrelationships between them. From these two definitions, we can see that the IBI focuses on the benefit of the buildings' owner and their desired indoor environment, while the EIBG one concentrates on creating the desired environment for the buildings' users (Nguyen and Aiello 2013).

Nevertheless, both definitions focus on the human factor and the techniques used to meet their comfort needs while on the same time having a positive environmental and economic impact.

Based on the aforementioned definitions, an IB can be described by 10 'Quality Environment Modules (QEM) (So et al. 2011):

- M1 Environmental friendliness—health and energy conservation
- M2 Space utilization and flexibility
- M3 Cost effectiveness—operation and maintenance with emphasis on effectiveness
- M4 Human comfort
- M5 Working efficiency
- M6 Safety and security measures—fire, earthquake, disaster and structural damages, etc.

M7 Culture
M8 Image of high technology
M9 Construction process and structure
M10 Health and sanitation.

Based on these 10 key modules, the Intelligent Building can be defined as one which is 'designed and constructed based on an appropriate selection of 'Quality Environmental Modules' to meet the user's requirements by mapping with appropriate building facilities to achieve long term building values (Wong and Wang 2005).

According to the two above-mentioned definitions developers and managers of a building should choose very carefully the kind of building they want to construct to be able to meet the demands of its users, which constantly change. Energy efficiency and environmental friendliness are among the most important demands an IB should cover. It should also be able to self-adapt according to the external and internal conditions to satisfy the needs of its users.

3.2 How to create an intelligent building

Even after defining the term "Intelligent Buildings" there is one question that still remains; how can a building be transformed into an intelligent one?

While trying to answer this question we discovered that intelligence does not always mean advanced technological systems. There are buildings that are intelligent and do not depend on information and communication technology (ICT) tools, or buildings that have state of the art technology integrated and are far from intelligent. The reason for this is because without efficient management of its components a building is but a high energy cost and environmentally hazardous machine. So, increasing the energy efficiency through the most effective use of the building's automation components alongside with the use of renewable energy sources is a very important and promising research field. For this reason, our research makes use of the third category of definitions and attempts to provide a comfortable environment for the buildings occupants while on the same time it saves the largest possible amounts of energy (Mpelogianni and Groumpos 2015).

According to Fillippin and Larsen (2007) the research on energy efficiency and Renewable Energy Sources in buildings focuses on the following topics:

1. *Solar collectors for air and water heating* the development of collectors that produce more and cost less. Old materials are replaced with new ones (e.g. replace glass with new, next generation plastics, or the use of optical coatings to increase the solar radiation absorbance) to create collectors that work in higher temperatures thus having higher thermal performance.
2. *Small scale solar cooling units* nowadays air conditioning is no longer considered as a luxury but rather as device necessary in every building. The air conditioning volumes, however, are responsible for the continuous increase of the electricity peak loads. For this reason, researchers have focused their efforts on developing high efficiency integrated systems of small scale, low price, high performing cooling systems which are going to replace the existing ones.
3. *Development and demonstration of standardized building components* this topic includes the efforts of developing and demonstrating components like photovoltaics that can be integrated into buildings. For this reason, a large number of researchers alongside with architects are creating building components which comply with existing standards and building codes, efficient façade panels, solar collector walls, double skin facades, and so on. The ultimate goal is to create building technologies that will be adopted by the market.
4. *Software for building simulation* meaning the development of computer programs that can calculate the temperature, ventilation, lighting, and energy needs of buildings. The software developed should give the ability to simulate the thermal behavior of the building by taking into consideration all the parameters that affect it such as the climatic conditions, geometry, materials, etc. Nowadays, a wide variety of programs with different complexity levels have been created to this end, some of them are: TRNSYS, Energy Plus, TAS Building Designer, SIMEDIF, etc.
5. *Integration of renewable energy supply* this topic focuses on the integration of external energy supply with self-supply from renewable energies, adjusted to different building types and climate zones. The goal is to drastically reduce the dependence on conventional energy sources.

Our research attempts to add a new topic to this category. Our objective is to take advantage of all the existing tools and equipment and combine them using human cognition processes, thus creating controllers that will optimally combine the various parts of a building's automation and achieve the higher energy savings with the lowest possible cost. For this purpose, we will use the fuzzy cognitive maps method and re approach it to increase the knowledge of a system.

4 Fuzzy cognitive maps

Fuzzy cognitive maps (FCMs) constitute a computational methodology that can examine situations during which the human thinking process involves fuzzy or uncertain descriptions. A FCM presents a graphical representation through a signed directed graph with feedback consisting of nodes and weighted arcs (Groumpos and Stylios 2000). The nodes of the graph stand for concepts that are used to describe, via cause and effect, the relations and behavior of a system in a simple and symbolic way. They are connected by signed and weighted arcs which represent the causal relationships that exist between the concepts (Fig. 2). Each concept, C_i (variable), is characterized by a number that represents its value and is calculated through the transformation of a fuzzy value to the interval [0,1]. The values of the interconnections', weights, are initially linguistically defined by experts and then transformed into values which belong to the interval $[-1,1]$ through a specially designed algorithm (Groumpos 2010). In this way, FCMs embody the accumulated knowledge and experience from experts who know how the system behaves in different circumstances.

The sign of each weight represents the type of influence between concepts. There are three types of interconnections between two concepts C_i and C_j:

- $W_{ij} > 0$, an increase or decrease in C_i causes the same result in concept C_j.
- $W_{ij} < 0$, an increase or decrease in C_i causes the opposite result in C_j
- $W_{ij} = 0$, there is no interaction between concepts C_i and C_j

The degree of influence between the two concepts is indicated by the absolute value of W_{ij}.

During the simulation, the value of each concept (A_i) is calculated using the following rule:

$$A_i(k+1) = f\left(A_i(k) + \sum_{j=1, j\neq i}^{n} A_j(k) w_{ji}\right), \tag{1}$$

where k represents the iteration step, n is the number of concepts and f is the sigmoid function given by the following equation:

$$\frac{1}{1+e^{-\lambda x}}, \tag{2}$$

where $\lambda > 0$ determines the steepness of function f.

The FCMs' concepts are given some initial values. Then the values of the concepts are calculated using Eq. 1. This iterative process ends when a steady state is achieved; the concepts' values converge to a single value (Axelrode 1976; Wong et al. 2005; Anninou et al. 2013; Papageorgiou et al. 2004; Papageorgiou and Stylios 2008).

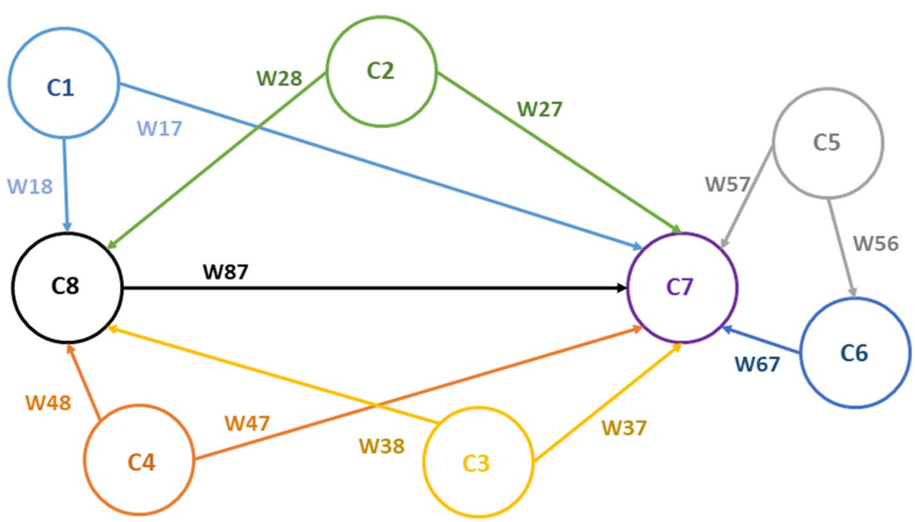
5 Re approaching FCMs

As stated in the introduction the FCMs is a modeling methodology which is very promising when we need to model complex systems, which are highly non-linear and involve fuzzy or uncertain situations. However, with the current modeling approach, various drawbacks emerge. These drawbacks dictate the need to use a new FCMs approach; while at the same time keeping the core of the method intact.

5.1 Limitations of fuzzy cognitive maps

These above-mentioned limitations; lack of knowledge of the system, dependence on experts, disability of self-learning, definition of the causality, calculation equation, ignorance of time factor, use of the sigmoid function-interpretation of the results, concern various steps of the method. In this subsection, we are going to list and analyze the ones that we are going to address and propose a new approach which will improve the Fuzzy Cognitive Maps methodology. But before we begin, we should state that even if some of the aforementioned drawbacks appear to be independent each one is connected to the other.

Fig. 2 Fuzzy cognitive map



The first limitation concerns the method of calculation of the values of the concepts, (Eq. 1). The calculation equation takes into consideration the change that each concept causes separately instead of the total change which is caused to the concept C_i. This results in a large increase to the value of the concept, that goes far beyond the interval [0,1].

This is the reason why the sigmoid function (Eq. 2) is needed; to fit the result to the interval [0,1]. But due to the shape of the curve (Fig. 3) any concept which, because of the additive calculation method (Eq. 1) is assigned a value beyond 3 leads the sigmoid function to correspond it to the value 1 which is greatly problematic as the final output is interpreted as “high” even if this is not always the expected or correct result.

Continuing on the subject of the sigmoid function there is another drawback that leads to high output values. This is the fact that the center of the curve instead of being on the (0,0) point on the *xy* axis it is on the (0.5,0) point. This means that each concept’s lowest value can be the 0.5. This problem combined with the first one makes it difficult to interpret the result even with the use of the experts’ interpretation criterion (Eq. 3).

$$R(x) = \begin{cases} 0, & x < 0.5 \\ \frac{x-0,5}{0.5}, & x > 0.5 \end{cases}. \tag{3}$$

Another problem that demands our attention is the fact that some concepts are not being affected by others thus they have to stay static through the whole iteration process. However due to the current sigmoid function (Eqs. 2) and (1) their value changes after the first iteration.

Finally, the last drawback that we would like to draw attention to, is that with the classic FCMs the concepts values converge to the same equilibrium point regardless of their initial conditions (Karagiannis and Groumpos 2013).

These problems dictated the need to have a new approach concerning the modeling of fuzzy cognitive maps.

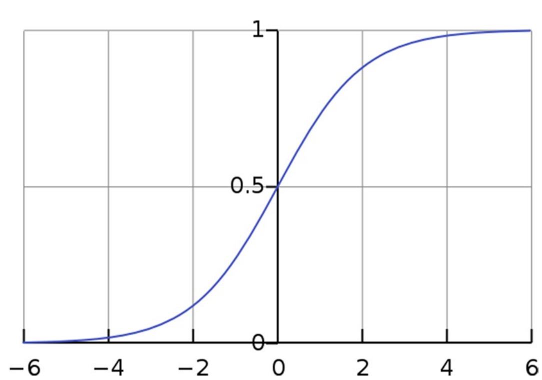


Fig. 3 Sigmoid function (Eq. 2)

5.2 A new approach in modeling FCMs

This new approach is going to be described in detail thought this subsection.

5.2.1 Improving the knowledge of the system

In the classic FCM approach, concepts represent the parameters of a system. These concepts are treated in the same way regardless of their nature. However, in a system even when it is described in a fuzzy way through a FCM it is still characterized by inputs, states and outputs. Since a FCM is a representation of such a system, we should take these characteristics into consideration. Ignoring the nature of each concept and treating all the concepts in the same way would cause problems regarding not only the calculation of their values but the overall knowledge of the system’s behavior. For this reason, we will use the representation of the classic control theory methods to separate the concepts of a fuzzy cognitive map into the following three categories (Ogata 1967)

State concepts:	The concepts describing the operation of the system, x.
Input concepts:	The inputs of the system, u.
Output concepts:	The concepts describing the outputs of the system, y.

A simple representation of the system can be seen in the following Figure 4.

In this way, we gain a better knowledge of the system. The proposed separation facilitates not only the understanding of the system’s operation but also the calculation of the concepts’ values.

5.2.2 Concepts’ variation

When describing the cause and effect between two concepts we investigate the change (increase or decrease) caused to one concept (C_2), when a change (increase or decrease) is caused to another concept (C_1). For this reason, we propose to change the way the effect of the other concepts is calculated by replacing the term $A_j[k]$ in the calculation equation (Eq. 1) with the term $\Delta A_j[k]$ which shows the change caused to each concept ($A_{new}-A_{previous}$). In this way, we can calculate more accurately the variation caused to one concept by all the others and also the results are in most cases within the desired interval (Vergini and Groumpos 2016). What is more to calculate the total change caused by all the other concepts to the one in question, we are going to use the following equation (Eq. 4) (Mpelogianni and Groumpos 2016a, b June):

$$\text{Total variation} = \frac{\sum_{j=1, j\neq i}^{n} \Delta C_j[k] w_{ji}}{\sum_{j=1, j\neq i}^{n} w_{ji}}. \tag{4}$$

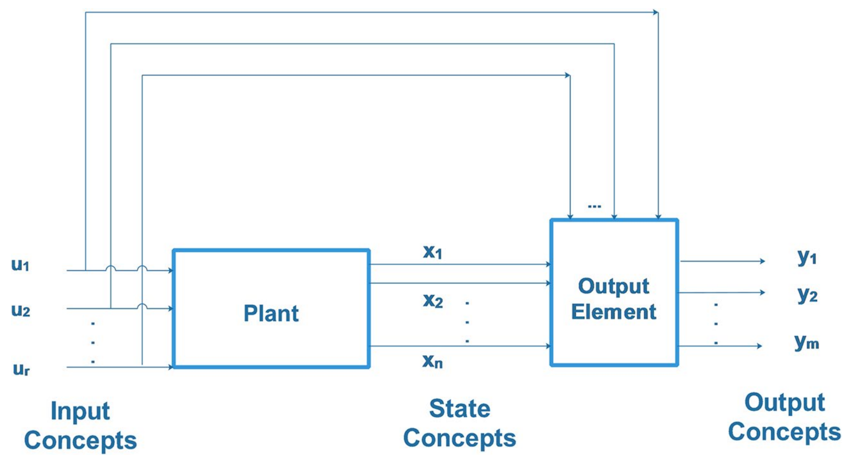


Fig. 4 Block diagram of the separated concepts

5.2.3 Calculation equations

Separating the concepts into categories gives us the ability to calculate their values in a different and more distributed way. For this reason, apart from the separation of the concepts we used the state space approach for one more reason, that of the calculation of their values. After having separated the concepts it became evident that the weight matrix can be divided into smaller ones to correspond them to each concept category. The classic equations

$$x_{k+1} = Ax_k + Bu_k,$$

$$y_k = Cx_k + Du_k,$$

are now used to calculate the variation caused by the change in the input and state concepts to the state and output concepts at each time step (k).

In this representation, A, B, C and D are individual weight matrices derived from the initial, defined by the experts, weight matrix.

The elements of A depend on the states' weights and the elements of B show how each input concept affects the state concepts of the system. C shows how the output concepts are related to the state concepts and D shows how the input concepts directly affect the output concepts (Ogata 1967).

5.2.4 Time versus iteration step

When using the classic FCM method to calculate the value of a concept, an iterative process is needed, and for this reason the k term in (Eq. 1) represents the time step. In this approach, we are going to differentiate the iteration step (n) from the time step (k). In most cases, the iteration process is no longer needed, however, in such a case when we need to insert a delay to give the state concepts the opportunity to interact with each other we can use an iterative process. This process will be terminated when the variation between two consequent values is very close to zero.

5.2.5 Interpretation of results

As mentioned above the use of the sigmoid function is to suppress the values of the concepts back to the [0,1]. The sigmoid curve, however, necessary, causes a number of drawbacks (concepts calculation and suppression, same equilibrium point etc) to our model. To solve those drawbacks, we propose that instead of using the sigmoid function we should use a membership function to correspond the crisp values to linguistic variables.

Finally, depending on the type of the output we can use the appropriate membership functions to translate the result to the appropriate form.

The above-mentioned changes are mathematically described by the following equations.

$$x_{k+1} = x_k + \frac{\Delta x_{k+1}}{\sum_{j=1, j\neq I}^{n} \left| W_{ji} \right|}, \tag{5}$$

$$y_{k+1} = y_k + \frac{\Delta y_{k+1}}{\sum_{j=1, j\neq I}^{n} \left| W_{ji} \right|}, \tag{6}$$

where

$$\Delta x_{k+1} = A\Delta x_k + B\Delta u_k, \tag{7}$$

$$\Delta y_{k+1} = C\Delta x_k + D\Delta u_k, \tag{8}$$

In this representation, Δx_{k+I}, Δx_k, Δy_k and Δu_k are column and row vectors that contain the variation of the state, output and inputs concepts, respectively.

After calculating the variations using (Eqs. 7) and (8) we use equations (Eqs. 5) and (6) to calculate the final values of the concepts.

In the following sections, we are going to use a model for the energy management of a building to show how the proposed model improves the study of a system using fuzzy cognitive maps.

6 Building automation and consumption modeling

6.1 The model

The lack of operational intelligence in home energy management has made the scheduling of multiple devices more complex and the manual device control inefficient and unattractive to the residents. Home energy management needs to be smart enough to optimize the best use of available power to the appliances for optimal consumption. In this paper, we present an intelligent home energy model which through the use of climate data calculates the expected operation of the building's automation (lighting, ventilation, air-conditioning) as well as the expected consumption of the building and finally decides whether the extra load should be run or scheduled for an off-peak hour, to reduce the energy consumption.

For the purpose of this paper, we will consider a system with inputs: the internal and optimal temperature (degrees Celsius—°C), the internal and optimal air quality (parts per million—ppm), the internal and optimal luminance (lux), the amount and the type of the extra load (kW) and finally the hour the system is currently operating (Mpelogianni and Groumpos 2016a, b).

The system's purpose will be to decide whether to run or to schedule the loads for another hour.

For this aim, it will utilize the following steps:

- *Step 1* The system will calculate the differences between the internal and optimal value for the temperature, the air quality and the luminance.
- *Step 2* It will decide on the operation of the building's automation (lighting, air conditioning and ventilation).
- *Step 3* Based on the previous calculations and the extra load that wants to be added to the system (building), will calculate the overall consumption of the building.
- *Step 4* Based on the consumption, the type of the extra load and the type of the hour it shall make the final decision; to run the load or schedule it for another hour.

6.2 Fuzzy cognitive map construction

In this part of the paper, we are going to create the FCM for modeling the system described above. Based on the description made in Sect. 5 of the paper we are going to divide the concepts of the FCM into inputs, states and outputs. The inputs will be the concepts that are not affected by any other concept but affect the states and outputs of the system. The state concepts will be the ones that are affected by the inputs or other state concepts and affect the output. Finally, the output concepts will be the ones that are calculated through the combination of the above-mentioned concepts.

6.2.1 Concept definition

The concepts as well as the category they belong to are listed below:

STATES

- *C1: ventilation*, the operation of the building's ventilation
- *C2: lighting*, the operation of the building's lighting
- *C3: air-conditioning*, the operation of the building's air-conditioning

INPUTS

- *C4: steptemp*, the difference between the internal and optimal temperature
- *C5: stepair*, the difference between the internal and optimal air quality
- *C6: steplum*, the difference between the internal and optimal luminance
- *C7: rthq*, the thermal quality of the room
- *C8: extraload*, the amount of extra load that is about to be added to the system

OUTPUTS

- *C9: consumption*, the consumption of the building

6.2.2 Interconnections' specification

Continuing the interconnection weights between nodes will be defined. This process will be undertaken by experts (electrical, mechanical, civil engineers) who in cooperation with each other will decide the interconnection weights. The values positive or negative will vary between the following ones:

- W (weak): Weak interconnection between the nodes C_i, C_j
- M (medium): Medium interconnection between the nodes C_i, C_j
- S (strong): Strong interconnection between the nodes C_i, C_j
- VS (very strong): Very strong interconnection between the nodes C_i, C_j

These values will then be defuzzified (Wong et al. 2005), (Runkler 1996) and a corresponding numerical value will be assigned to each one of them.

The initial weight matrix of the system is shown in Table 1.

According to the separation of the concepts we can form the *A*, *B*, *C* and *D* matrices as follows.

Table 1 Weight matrix

	*C*1	*C*2	*C*3	*C*4	*C*5	*C*6	*C*7	*C*8	*C*9
*C*1	0	0	0.12	0	0	0	0	0	1
*C*2	0	0	0	0	0	0	0	0	1
*C*3	0	0	0	0	0	0	0	0	1
*C*4	0	0	0.98	0	0	0	0	0	0
*C*5	0.98	0	0	0	0	0	0	0	0
*C*6	0	0.9	0	0	0	0	0	0	0
*C*7	0	0	−0.5	0	0	0	0	0	0
*C*8	0	0	0	0	0	0	0	0	1
*C*9	0	0	0	0	0	0	0	0	0

$$A = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0.12 & 0 & 0 \end{bmatrix},$$

$$B = \begin{bmatrix} 0 & 0.98 & 0 & 0 \\ 0 & 0 & 0.9 & 0 \\ 0.98 & 0 & 0 & -0.5 \end{bmatrix},$$

$$C = \begin{bmatrix} 1 & 1 & 1 \end{bmatrix}$$

$$D = \lceil 1 \rceil$$

After the defuzzification process, we can create the fuzzy cognitive map, which is presented in Fig. 5.

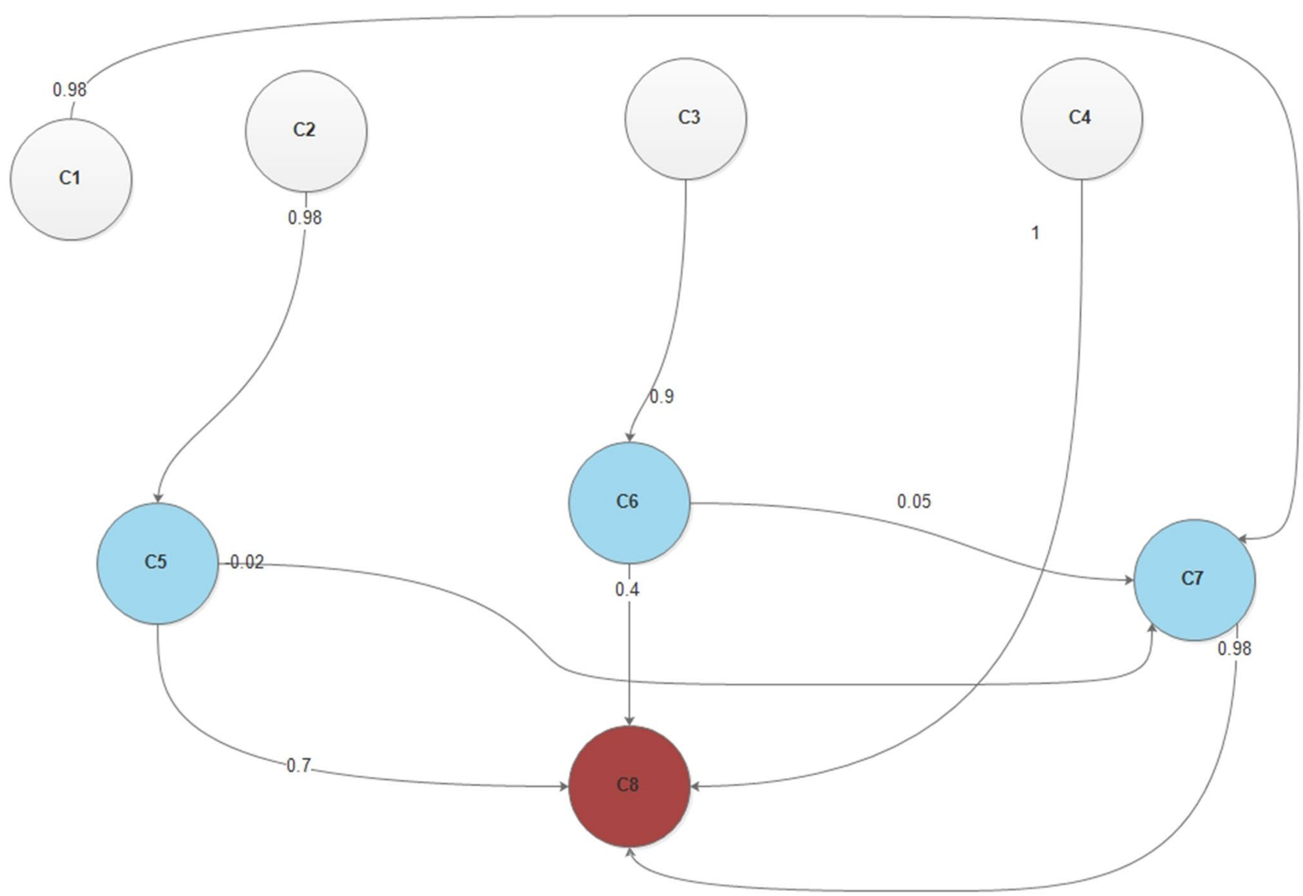


Fig. 5 System's fuzzy cognitive map

7 Results

To understand this process and to explain the differences between the two methods we will examine two different case studies, for two sets of inputs. These are presented below (Table 2):

Based on these inputs the algorithm will correspond the appropriate values to the concepts according to the membership function shown in Fig. 6.

Via the above membership function and the center of area (COA) defuzzification technique, derive the initial values for the input concepts.

Case study 1: 1.00, 0.00, 1.00, 1.00, 0.50.

Case study 2: 1.00, 0.66, 0.00, 0.10 ,1.00.

For the purpose of this study, we will assume that all the initial values of the state concepts are zero.

Table 2 Inputs

Inputs	Case study 1	Case study 2
Internal temperature	35	30
Optimal temperature	25	27
Internal air quality	900	1000
Optimal air quality	800	700
Internal luminance	100	300
External luminance	500	500
Extra load	2	4
Room thermal quality	Very Good	Poor
Extra load type	Critical	Schedulable
Hour type	Peak Time	Peak Time

7.1 Results of the existing FCM model

In the first simulation, we used the classic FCMs model the initial vector C which has the values for all the concepts is:

*C*initial = [1 0 1 1 0.5 0 0 0 0].

After a few iterations, the system reaches equilibrium and the final vector *C* will be:

*C*final:

[0.6591 0.6590 0.6591 0.6590 0.6590 0.8110 0.8013 0.6697 0.9594].

However, even if we change the inputs to.

*C*initial = [1 0.66 0 1 0 0 0 0].

and run the process again we take the same result.

*C*final:

[0.6591 0.6590 0.6590 0.6591 0.6590 0.8111 0.8013 0.6696 0.9594].

As we can see even the input concepts (the first four values) reach the same steady state. This happens because of the sigmoid function. While necessary to be able to reach a steady state because of its non-linear nature the sigmoid function creates some drawbacks. What is more because the center of this function is the (0,0.5) we need an interpretation criterion to take the final values of the system. In our case, we used the one described by (Eq. 3).

Where x is the final value of the concept and $R(x)$ the final value of the system.

7.2 Results of the new approach

Continuing our experiments, we will study the case when we use the new approach.

Case study 1:

Initial variation of the states

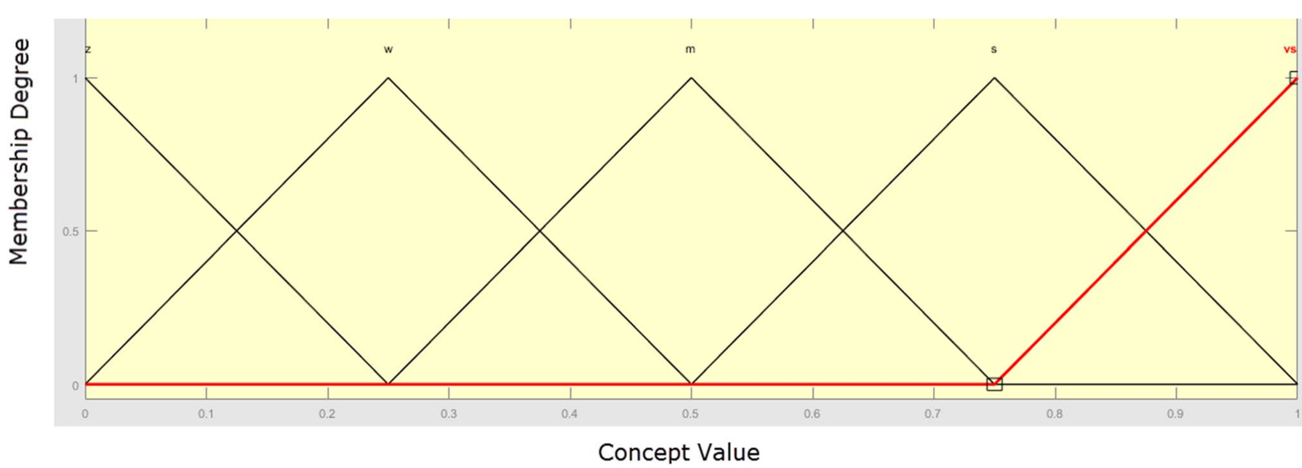


Fig. 6 Inputs defuzzification

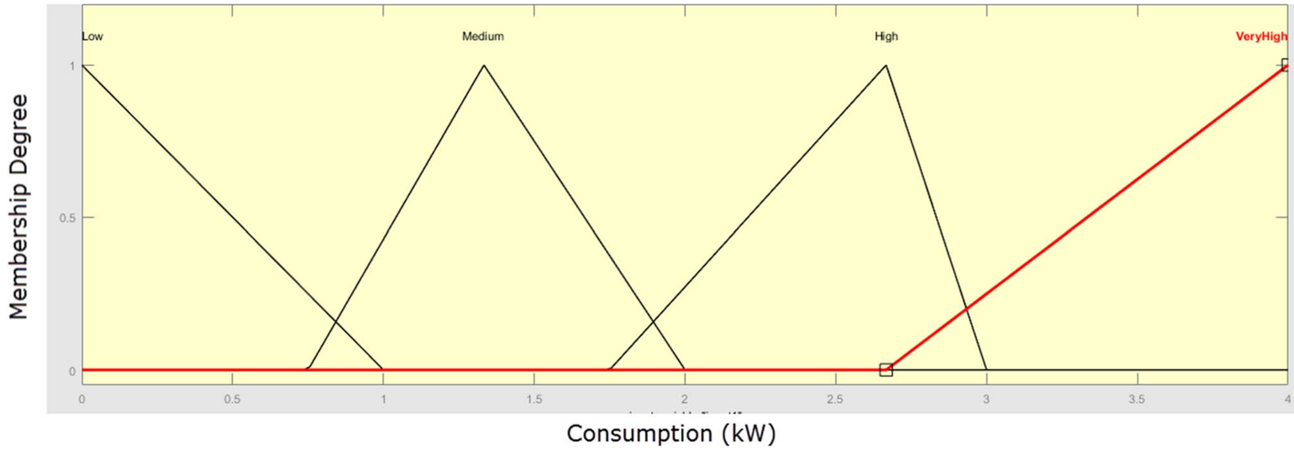


Fig. 7 Consumption fuzzification

$$\Delta x_0 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

Initial variation of the Inputs that affect the states

$$\Delta u_0^1 = \begin{bmatrix} 1 \\ 0 \\ 1 \\ 1 \end{bmatrix}$$

Initial variation of the Inputs that affect the output

$\Delta u_0^2 = [0.5]$

Case study 2:

Initial variation of the states

$$\Delta x_0 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

Initial variation of the Inputs that affect the states

$$\Delta u_0^1 = \begin{bmatrix} 1 \\ 0.66 \\ 0 \\ 0.1 \end{bmatrix}$$

Initial variation of the Inputs that affect the output

$\Delta u_0^2 = [1]$

After applying the above values to equations (Eqs. 4–8).

The final values for the first case study are.

$x = [0.0\ 1.0\ 0.17]$ and $y = [0.84]$.

and for the second.

Table 3 Final results

	Case study 1	Case study 2
Consumption	Low	Medium
Extra load type	Critical	Schedulable
Hour type	Peak time	Peak time
Load shifting	Run load	Shift load

$X = [0.66\ 0.0\ 1.79]$ and $y = [1.72]$.

To interpret these values which are beyond the desired interval we will use the following membership function (Fig. 7).

After assigning a linguistic value to the consumption we use a fuzzy rule to decide whether the extra load should be shifted or not.

The final results are shown in Table 3.

Through the observation of the results we can see that not only our calculations are far more accurate but also, we can identify the sources of high consumption in the building and address them, either by further adjusting the weights between the concepts to make the modeling methodology more efficient, or by taking actions regarding the operation of the building such as the load shifting in the second case study. Overall, we have achieved the minimization of the consumed energy especially in the first case study where the consumption of the air conditioning unit is very low.

8 Conclusion and future research

8.1 Conclusion

As stated in the introduction and analyzed in Sects. 2 and 3, the world undergoes a severe energy crisis. This crisis is largely affected by the high amounts of energy consumed by the building sector. To address this severe problem scientists have gathered their efforts in developing software and equipment that can reduce the energy consumed as well as take advantage of the renewable energy sources. These new sophisticated tools have inevitably led to the arise of a new scientific sector that of intelligent buildings.

In this paper, we have analyzed the term of IBs and decided to make an anthropocentric approach. Our efforts focused on modeling an intelligent building while trying not only to combine efficiently the various parts of its automation but also by trying to meet the needs of its occupants; reduced energy bills, better living conditions. For this reason, we used the method of fuzzy cognitive maps and re-approached them thus increasing their accuracy in modelling complex dynamic systems (CDS).

As a result of this study, well-known limitations of FCMs were addressed and a new mathematical approach in modeling FCMs was proposed and developed. This approach combines the state space approach of the system to help improve the existing method of FCMs. The new equations which were formulated are introduced and mathematically justified.

Specifically The separation of concepts in states, inputs and outputs was proposed to increase the knowledge of the system. Based on this separation new calculation equations were introduced which gave more accurate results. What is more with the addition of the membership functions in the interpretation of the results, the limitations of the use of the sigmoid function were surpassed while at the same time the system maintained its non-linear nature.

Finally, by implementing the new approach (increased knowledge and more accurate calculations) to a system for the calculation of the consumption of a building and the control of its load we managed to keep the overall consumption into minimum levels, contributing in this way to the energy reduction problem via the efficient use of the building's automation.

8.2 Future research

Our goal is to continue our research and focus our efforts on making the proposed approach even more complete. Moreover, we plan to apply the method in even more complex systems, as well as use new learning techniques in order be able not only to model but also to control these systems so as to meet people's needs.

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